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Multi-Level Region Matching for Fine-Grained Sketch-Based Image Retrieval

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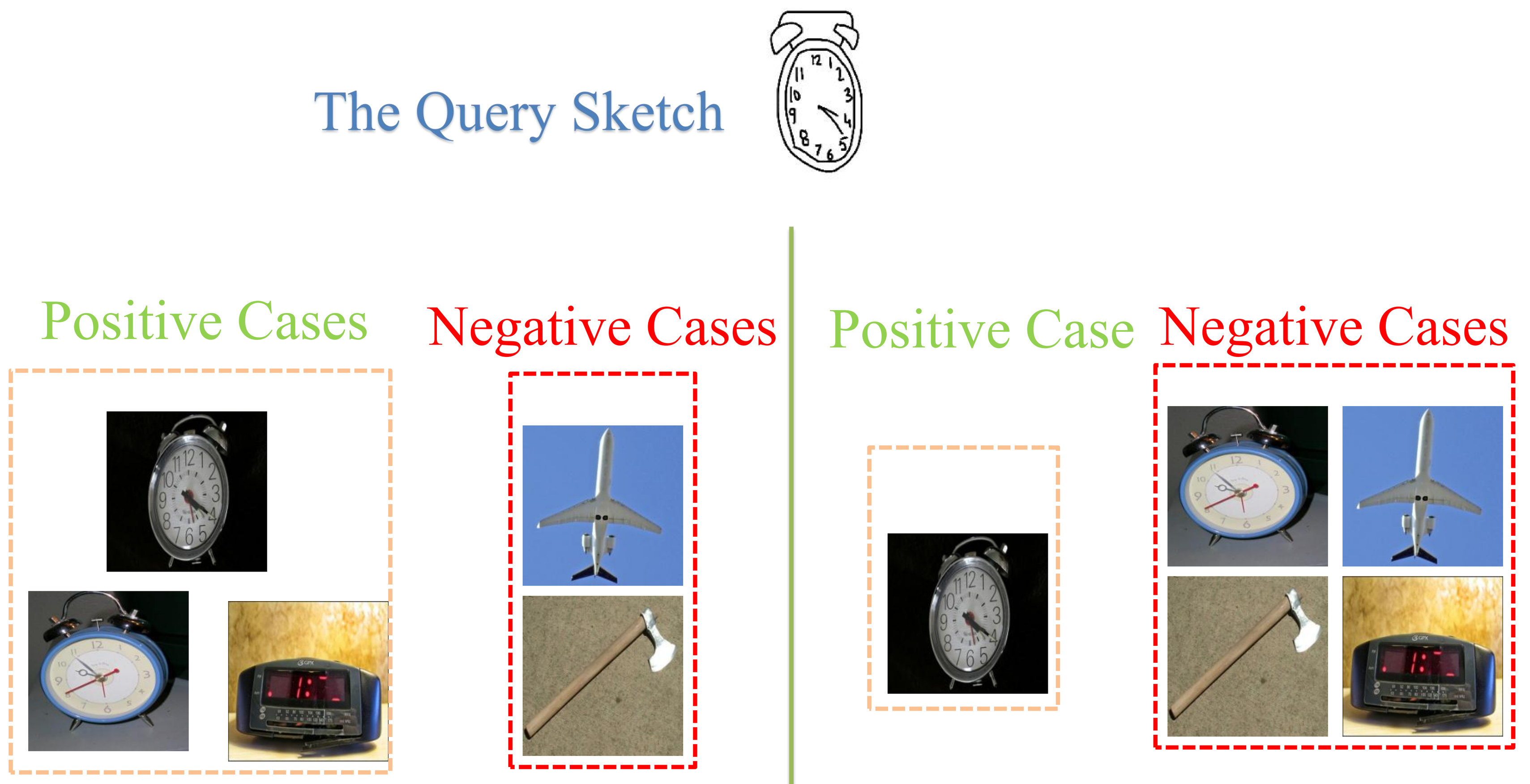
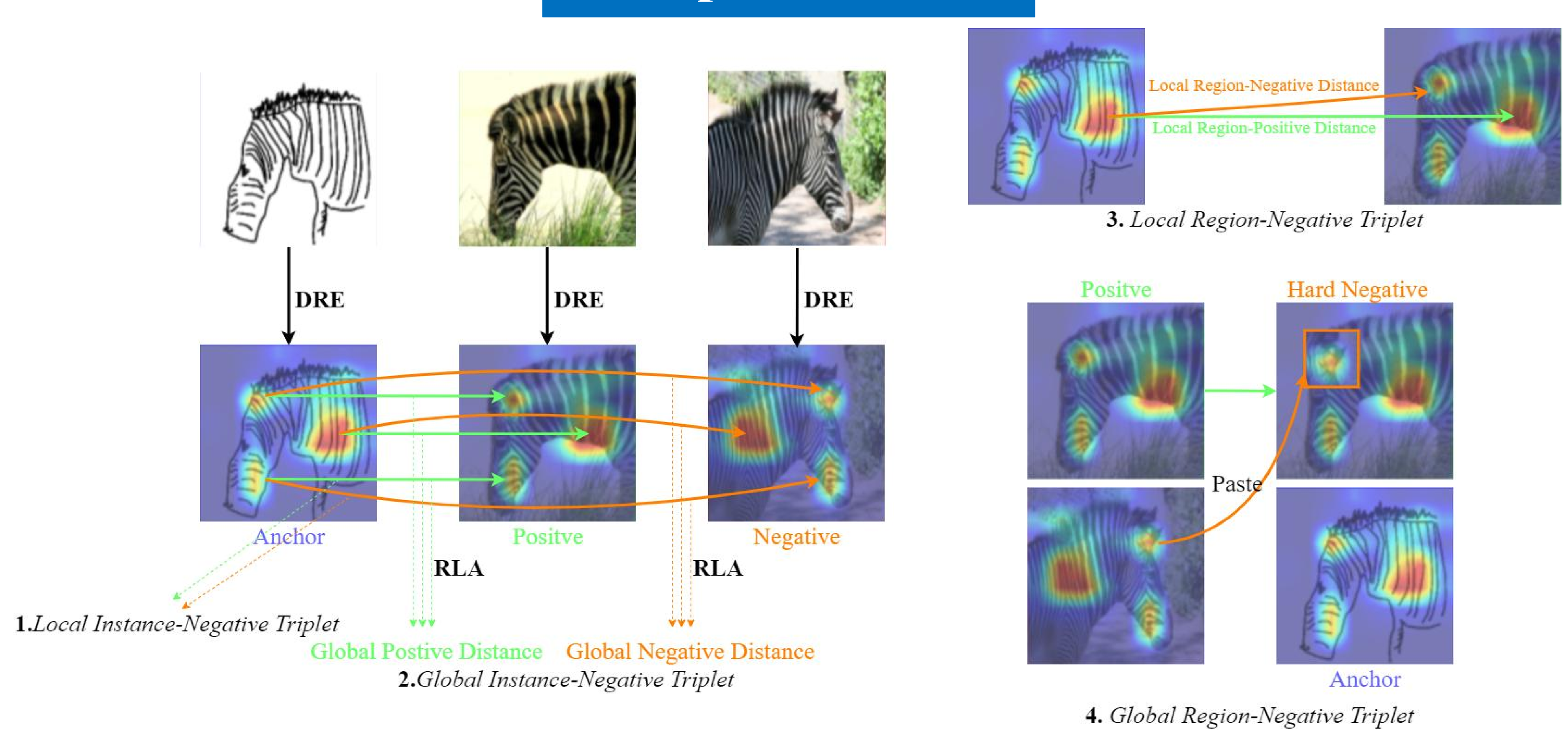
Task Setting



Coarse-Grained Sketch-Based Image Retrieval (**CG-SBIR**)

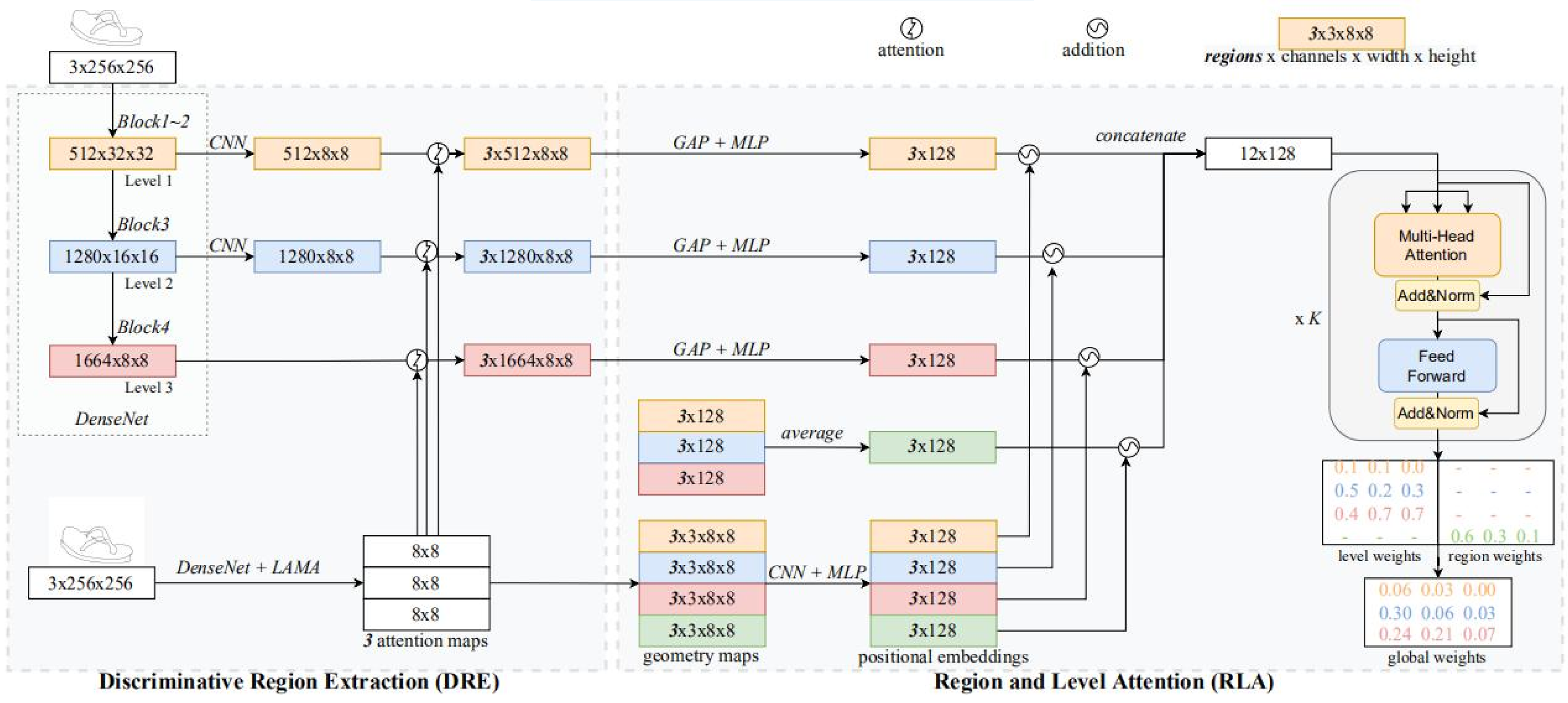
Fine-Grained Sketch-Based Image Retrieval (**FG-SBIR**)

Triplet Losses



Triplet loss 1: $\mathcal{L}_{gtrp-in}$ targets at semantic correspondence between paired regions.
Triplet loss 2: $\mathcal{L}_{gtrp-rn}$ targets at global matching distance.
Triplet loss 3: $\mathcal{L}_{ltrp-in}$ targets at semantic distinctiveness across unpaired regions.
Triplet loss 4: $\mathcal{L}_{ltrp-rn}$ targets at hard negative samples.

Framework



Overview of the proposed MLRM

- In DRE, we propose a LAMA structure to extract different attention maps to attend multi-level CNN feature maps.
- In RLA, we adopt a transformer-based attentive matching module to obtain attention weights for different regions and levels.
- At last, we aggregate region/level-wise distances by weights as a retrieval distance.

LAMA *v.s.* CAMA

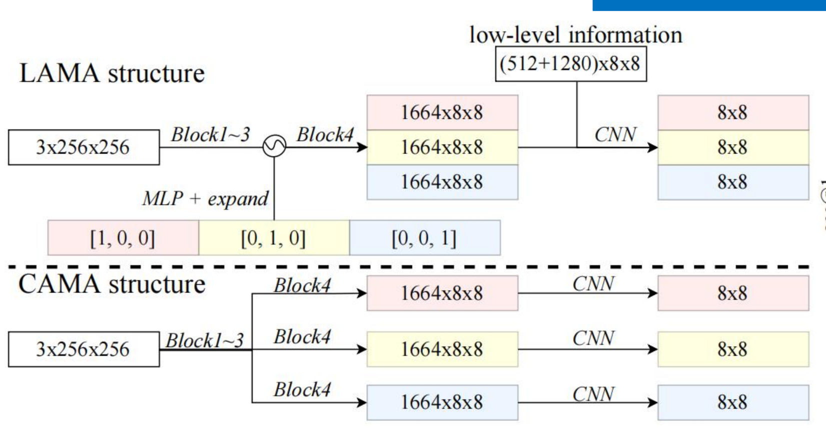


Figure 2: LAMA and CAMA structure.

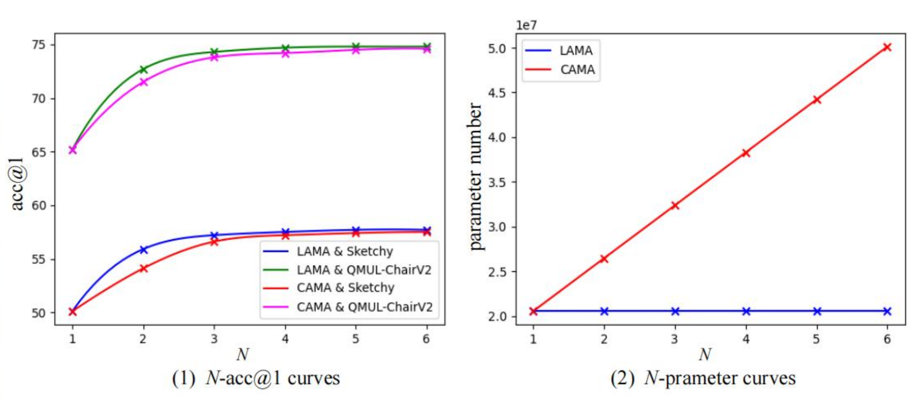
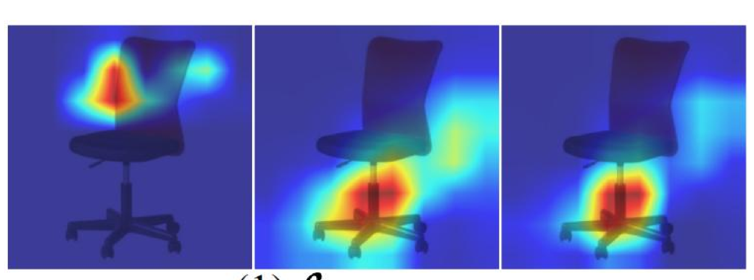


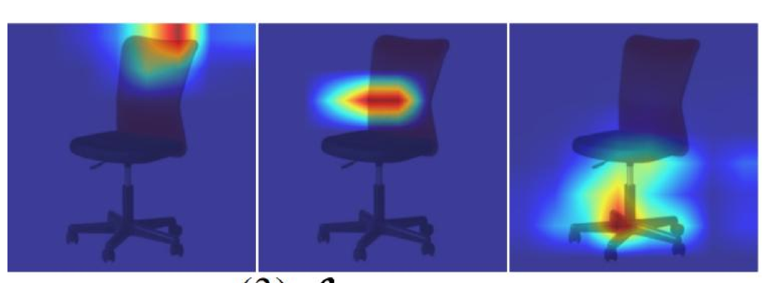
Figure 4: LAMA and CAMA quantitative comparison.

$$\mathcal{L}_{ovl-cama} = \frac{1}{N}\sum_{x,y} M_1 \odot M_2 \odot \cdots \odot M_N,$$

$$\mathcal{L}_{ovl-lama} = \frac{1}{N\times N}\sum_{r\le N}\sum_{x,y} M_r \odot MaxPool(\prod_{r'\ne r, r'\le N} M_{r'})$$



(1) $\mathcal{L}_{ovl-cama}$



(3) $\mathcal{L}_{ovl-lama}$

- Inspired by CAMA, we propose LAMA to extract discriminative regions.
- LAMA merges different network branch copies into one, saving a large number of parameters when improving model performance.
- LAMA adopts an improved overlapping penalty, learning better geometrically discriminative regions.

Experiments

	Sketchy (%)	QMUL-ChairV2 (%)	QMUL-ShoeV2 (%)	QMUL-Chair (%)	QMUL-Shoe (%)
Song *et al.* [32] (CVPR '16)	-	-	-	78.4	50.4
GN Triplet [29] (TOG '16)	37.1	-	-	-	-
SaN Triplet [42] (CVPR '16)	36.2	56.6	30.9	72.2	52.2
Quadruplet [30] (ACM MM '17)	42.2	-	-	-	-
DSSA [33] (ICCV '17)	-	-	33.7	81.4	61.7
Radenovic *et al.* [27] (ECCV '18)	-	-	-	85.6	54.8
DCCRM [40] (PR '19)	46.2	-	-	-	-
TC-Net [19] (ACM MM '19)	40.8	65.3	40.2	95.9	63.5
Bhunia *et al.* [5] (CVPR '20)	-	(89.7)	(79.6)	-	-
Pang *et al.* [26] (CVPR '20)	-	-	36.5	96.0	56.5
Bhunia *et al.* [3] (CVPR '21)	-	60.2	39.1	-	-
LA [37] (ACM MM '21)	43.1	64.8	42.3	93.8	57.4
DLA [37] (ACM MM '21)	54.9	69.2	50.2	**99.0**	**79.1**
Zhang *et al.* [43] (PR '22)	-	-	-	84.4	65.7
AE-Net [7] (PR '22)	46.0	-	-	-	-
Bhunia *et al.* [4](CVPR '22)	-	64.8	43.7	-	-
MLRM (ours)	**57.2**	**74.3(98.2)**	**50.4(87.9)**	**99.0**	67.0

Table 1: acc@1(acc@10) comparison with previous works.

		TC-Net[19]	LA [37]	DLA [37]	MLRM (ours)
QMUL-ChairV2	Time (s)	5.3	27.5	236.7	11.8
	acc@1 (%)	65.3	64.8	69.2	74.3
Sketchy	Time (s)	8.2	46.8	639.3	14.1
	acc@1 (%)	40.8	43.1	54.9	57.2

Table 2: Retrieval time comparison using the same GPU.

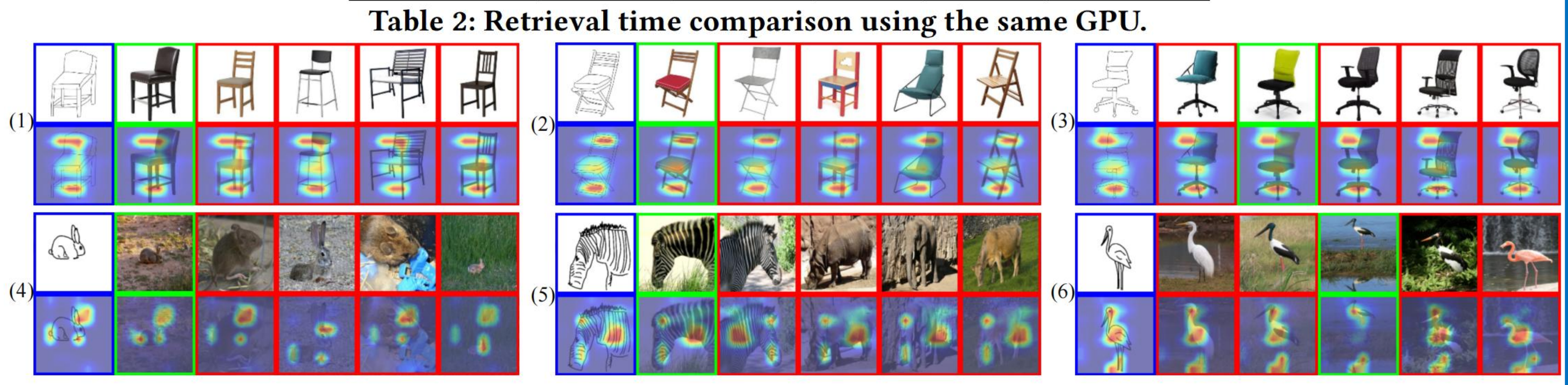


Figure 6: Top-5 retrieval visualization on QMUL-ChairV2(row (1)-(3)) and Sketchy(row (4)-(6)). The sketches bordered in blue are queries. The images bordered in green/red are positive/negative cases.

- Our MLRM achieved SOTA on all datasets except QMUL-Shoe, on which MLRM is the second best.
- Our MLRM does not introduce much extra computation overhead.
- Our MLRM can well extract both geometrically and semantically discriminative regions.

Conclusion

- To establish fine-grained correspondence between sketches and im_x0002_ages, we propose Multi-Level Region Matching (MLRM).
- MLRM consists of DRE that generates discriminative regions and RLA to obtain attention weights for different regions and levels.
- Comprehensive experiments have demonstrated that MLRM achieves SOTA acc@1 at the cost of a relatively low computation overhead.

Acknowledgements

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